Automated Colorization of Grayscale Images Using Texture Descriptors

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***Abstract*— A novel example-based process for automated colorization of grayscale images using texture descriptors (ACTD) without any human intervention is proposed. By analyzing a set of sample color images, coherent regions of homogeneous textures are extracted. A multi-channel filtering technique is used for texture-based image segmentation. For each area of interest, state of the art texture descriptors are then computed and stored, along with corresponding color information. These texture descriptors and the color information are used for colorization of a grayscale image with similar textures. Given a grayscale image to be colorized, the segmentation and feature extraction processes are repeated. The texture descriptors are used to perform Content-Based Image Retrieval (CBIR). The colorization process is performed by chroma replacement. This research finds numerous applications, ranging from classic film restoration and enhancement, to adding valuable information into medical and satellite imaging, and to enhance the detection of objects from x-ray images at the airports.**

***Computer vision*; Image colorization; Fuzzy C-means clustering; Gabor transform; CBIR**

I. Introduction

Image colorization has been performed through various means since the early 20th century, as a very laborious, time-consuming, subjective and painstaking manual. Its main purpose is to increase the visual appeal of old black and white photographs, motions pictures and illustrations. Current methods of image colorization can be classified into two different groups, Scribble-based and Example-based. Scribble-based colorization techniques require a user to scribble color information onto appropriate regions of the grayscale image, which is a time-consuming task [1]. The color information is then spread through the image via various algorithms. Example-based colorization techniques automate this process by providing an example image from which to extract the color information from [2][3][4]. This process can save a lot of time and requires little or no user interaction. However, the results can vary considerably depending on the example image chosen. Most techniques still require user input in the form of swatches, and use simple texture matching methods [3]. While the method suggested by Irony *et al.* [2] used a very robust monochrome texture matching method with spatial filtering, they suggested that better results could be obtained by using improved spatial coherence descriptors, such as the Gabor transform. Several other research papers also suggested that better segmentation could be achieved by using Gabor filters.

II. Previous work

A. Texture-based image segmentation

Accurately identifying the areas of homogeneous textures in an image is a key element of the colorization process. In order to effectively segment the image based on texture, Malik and Perona [5] suggested that a multi-channel filtering approach could be used. Jain and Farrokhnia [6] accomplished this by using a bank of two-dimensional Gabor filters.

B. Gabor Transform

A two-dimensional Gabor function consists of a sinusoidal plane wave of some frequency and orientation, modulated by a two-dimensional Gaussian. The convolution of an image with a bank of Gabor filters creates a set of filtered images containing features that responded to the particulate filter. Jain and Farrokhnia [6] suggested that feature extraction can be obtained by using a nonlinear sigmoid function, and by calculating the average absolute deviation (AAD) for each filtered image.

C. Clustering and Feature Extraction

Naotoshi [7] used Gaussian smoothing in order to remove the smaller areas, combined with a simple K-means clustering algorithm in order to extract regions from filtered images. The segmentation results were satisfactory but lacked accuracy. Texture-based segmentation was recently improved by Dong *et al.* [8] by using a Fuzzy C-Means (FCM) method to generate the index map and palette, and by using the Probabilistic Index Map (PIM) model to improve segmentation accuracy. Once a proper level of clustering has been obtained, smaller regions contained inside of a larger region can be removed. Isolated small regions of unique texture cannot be used and can also be discarded, and the remaining regions are labeled. Once each region is labeled, a sample area for each texture is extracted. This is done by finding the largest square that can be fitted into each identified contiguous region on unique texture. For each texture, the color descriptor (the dominant color as per the color histogram) and texture descriptors can be extracted and stored.

D. Content-Based Image Retrieval

CBIR, the ability to retrieve images by analyzing their content, is another research area that has received a lot of attention in recent years. Gabor transforms are also the central part of the Homogenous Texture Descriptor (HTD), which offers a simple yet powerful method for storing texture information for retrieval. HTD is part of the "Multimedia Content Descriptor Interface" of the MPEG-7 standard, which has been successfully used in the fields of Image

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Classification and Content-based image retrieval [9].The *img(Rummager)* [10] image retrieval system has implemented several descriptors that can be used to retrieve images in various situations. In this research, a new process for automated colorization is proposed by combining these techniques in a new and innovative way.

III. Automated Colorization Using Texture Descriptors (ACTD)

The first part of the process is to analyze several sample color images. In order to effectively segment the image based on texture, the multi-channel filtering approach suggested by Malik and Perona [5] was used. Gabor wavelet transforms have proven to be a very effective method for achieving accurate texture-based image segmentation. A clustering algorithm then needs to be used to segment the regions of homogeneous texture previously identified and extract a representative sample for each texture. The texture descriptors and color information can be computed for each texture, and stored in a database. The second part of the process assumes that a new grayscale image needs to be colorized based on the texture and color information present in the database. The segmentation and feature extraction process takes place as previously described. For each texture identified, the texture descriptors are computed, and used to locate the best matching texture present in the sample database. Once the best matching texture is identified, the corresponding color information is extracted, and applied to the segmented region of the grayscale image. Figure 1 shows an overview of the ACTD process used in this research.

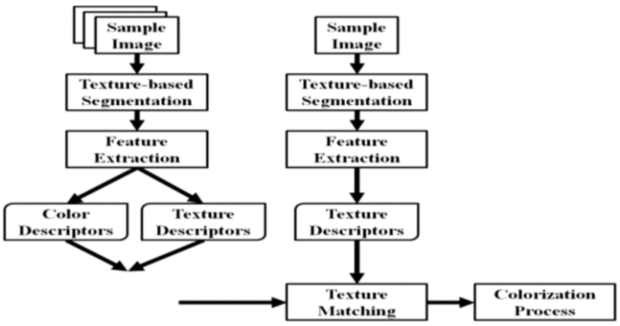

Figure 1. Architecture for ACTD

A. Texture-based Image Segmentation

In order to obtain a good texture-based segmentation of an image, the multi-channel filtering approach suggested by Malik and Perona [5] was used. This was accomplished by using a bank of two-dimensional Gabor function consisting of a sinusoidal plane wave of a given frequency and orientation, modulated by a two-dimensional Gaussian envelope. The Gabor filters were obtained using equation (1)

$$g(x,y;\lambda,\sigma,\gamma) = \exp\left(-\gamma \frac{x'^2+\gamma^2 y'^2}{\sigma^2}\right) cos\left(2\pi \frac{x'}{\lambda}\right) \quad (1)$$

$$x' = x\cos\theta + y\sin\theta \quad (2)$$

$$y' = -x\sin\theta + y\cos\theta \quad (3)$$

Where ó is the width of the Gaussian envelope, ã is the spatial aspect ratio, ë is the wavelength of the filter, and è is its orientation. Jain and Farrokhnia [6] achieved good feature extraction results by using a nonlinear sigmoid function and by calculating the average absolute deviation (AAD) for each filtered image. Gaussian smoothing was used in order to remove the smaller areas. In this research, smoothing was performed by calculating the mean values of the gray-level intensities between neighboring pixels. The Gabor response values for each pixel were added, and normalized.

B. Clustering

Jain and Farrokhnia used the K-means clustering algorithm to create and label the texture regions. The Fuzzy C-means clustering (FCM) algorithm can improve this process by allowing the concept of partial membership, in which an image pixel can belong to multiple clusters. This "soft" clustering allows for a more precise computation of the cluster membership.

C. Modified Fuzzy C-means clustering with "G_{ki} factor"

In order to improve the tolerance to noise of the Fuzzy C-means clustering algorithm, Krinidis and Chatzis [11] have proposed a new method by introducing the novel G_{ki} factor. The purpose of this algorithm is to adjust the fuzzy membership of each pixel by adding local information from the membership of neighboring pixels. It is obtained by using a sliding window of predefined dimensions used to compute the G_{ki} factor. The G_{ki} factor is calculated by using:

$$G_{ki} = \sum_{\substack{j\in N_i \\ j\neq i}} \frac{1}{d_{ij}+1}\left(1-\mu_{kj}\right)^m \left|x_j - v_k\right|^2 \quad (8)$$

Where the i^{th} pixel is the center of the local window, the j^{th} pixel in the window around the i^{th} pixel (N_i), k is the reference cluster, d_{ij} is the spatial Euclidian distance between pixels i and j. μ_{kj} is the degree of membership of the j^{th} pixel in the k^{th} cluster, v_k is the prototype of the center of cluster k, m is a fuzziness factor (a value > 1), x_i is the i^{th} pixel in N, $|x_i - v_k|$ is the Euclidean distance between x_i and v_k. This algorithm is minimized by using equation (4):

$$j_m = \sum_{i=1}^{N} \sum_{k=1}^{c} \left[\mu_{ki}^m |x_i - v_k|^2 + G_{ki}\right] \quad (4)$$

$$\text{where } v_k = \frac{\sum_{i=1}^{N} \mu_{ik}^m x_i}{\sum_{i=1}^{N} \mu_{ik}^m} \quad (5)$$

$$\text{and } \mu_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{|x_i - v_k|^2 + G_{ki}}{|x_i - v_{kj}|^2 + G_{ji}}\right)^{\frac{1}{m-1}}} \quad (6)$$

D. Feature Extraction

The contiguous region on unique texture enhanced by the Gabor filters and identified by the segmentation algorithm are then isolated and extracted. Blob filtering is used in order to remove the smaller clustered areas. The center of gravity of each blob is used to extract a sample image representative of that particular texture. The texture image is stored both in color for a reference to the color component (chroma) of the texture and in grayscale for texture matching.

E. Grayscale image processing

The segmentation and feature extraction processes are then repeated for the new grayscale image to be colorized.

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F. Texture Matching

Compact Composite Descriptors (CCD) is a recently proposed set of descriptors combining several features descriptors. These Descriptors are part of the new Visual Multimedia Content Description Scheme (VICODEs), which is proposing a set of specialized descriptors tuned for different types of images. Testing of these descriptors was performed using the *img(Rummager)* [10] application, using the MPEG-7 Edge Histogram Descriptor (EHD), the VICODEs (CCD) Fuzzy Spatial Based Scalable Composite Descriptor (BTDH) [12], and the VICODEs (CCD) Auto Descriptor Selector (ADS).

G. Grayscale Image Colorization

Once the proper segmentation is obtained and the proper colors are identified, placing the color in the proper areas of the test image can be achieved in the YCbCr color space. The advantage of this color space is that it separates the luminance (Y) component from the color components (Cb and Cr are the blue-difference and red-difference chroma components). Thus, it is possible to replace the chroma components while preserving the luminance information of the image. In this research, the chroma component of the test image is replaced with the colors corresponding to the matching textures from the library of images.

IV. EXPERIMENTAL RESULTS

Figure 4 shows the various stages of the colorization of a test image through the ACTD process.

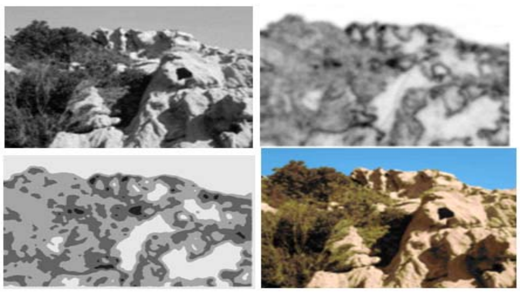

Figure 4. *(a)* Grayscale image, *(b))* Mean smoothing of the sum of Gabor responses, *(c)* Segmented regions, *(d)* Colorized image

V. CONCLUSION AND FUTURE WORK

A new and innovative method for automating example-based colorization process is implemented. This process combines several techniques from Digital Image Processing in order to improve the automation of the colorization process. This includes Gabor-based image segmentation combined with improved fuzzy C-means clustering, extraction and storage of the Texture and Color Descriptors, and a texture-based color retrieval technique. Colorization results in general are subjective and not easily quantifiable. Results obtained using this method are dependent on the number of textures present in the database and on the ability to find a suitable color match.

However, reasonably accurate results were obtained with a limited number of sample images. Several of the steps require custom parameters that can be tuned for different types of images, such as the Gabor wavelength and orientation, and the number of clusters.Since the textures extracted from each sample image have no preset size or shape, the Texture retrieval methods need to be improved for scale and rotation invariance, which would lead to a better accuracy rate. This method could also be enhanced to store more complete color descriptors in order to accommodate more complex textures containing multiple colors. These improvements would most likely improve the accuracy of the colorized images, the testing conducted as part of this research proved that the ability to combine these techniques in order to automatically colorize grayscale images is a viable option.

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